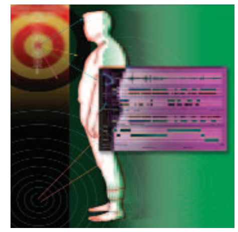
# Healthwear: Medical Technology Becomes Wearable



**Widespread adoption of sensors that monitor the wearer's vital signs and other indicators promises to improve care for the aged and chronically ill while amassing a database that can enhance treatment and reduce medical costs.**

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The concept of computing is rapidly expanding from simply using a desktop PC, where people sit and type for a small part of the day. Every day, more than one billion people carry around portable computation devices that have sensors and Internet-capable connections—but we call them cell phones rather than computers.

The most recent cell phones go far beyond telephony: They are truly wearable computers. These location-aware devices have sensors for detecting sounds, images, body motion, and ambient light level, have a secure Internet connection, and can download and upload programs as well as audio and image files. They also can serve as a situation-aware intelligent assistant, whether as personal agents that use the digital equivalent of 3M's Post-it notes to augment reality or as a means of forming tight-knit intellectual collectives in which people can supercharge their social networks.

As part of this change in the way we use computers, my research group at the MIT Media Lab (http://hd.media.mit.edu) has been developing *healthwear,* wearable systems with sensors that can continuously monitor the user's vital signs, motor activity, social interactions, sleep patterns, and other health indicators. The system's software can use the data from these sensors to build a personalized profile of the user's physical performance and nervous system activation throughout the entire day—providing a truly personal medical record that can, we believe, revolutionize healthcare.

## HEALTHWEAR OVERVIEW

Until recently, researchers have had little success in extending healthcare into the home environment, yet there clearly is a huge demand for this service. Americans currently spend $27 billion on healthcare outside the formal medical establishment because they find it difficult to access, expensive, and painful (www.rwjf.org). A clear demand for better integrating the home into the healthcare environment exists. Not only that, but a dramatic shift in the composition of the US population makes it absolutely necessary to develop such distributed systems.

### Caregiver shortage

Although the US had 25 caregivers for each disabled person in 1970, the success of our healthcare system will lower the ratio of caregivers to at-home disabled to 6 to 1 by 2030 (www.agingstats.gov). How will those six people care for a disabled person? Certainly, a centralized system of visiting nurses is not an option for providing this care—such a system would leave too few individuals working at other jobs in the economy to support it. Thus, a more highly distributed system is not only desirable, but absolutely necessary.

These statistics provide the driving force behind the development of healthwear. This concept offers an unobtrusive method for acquiring in-depth knowledge about the body that could help manage chronic medical conditions such as cancer, diabetes, degenerative disorders of the nervous system, or chronic pain. Perhaps just as importantly, the deploy-


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ment of continuous monitoring devices provides an excellent opportunity to fully inform medical providers about a patient's condition, thus helping the patient obtain the best treatment possible.

Already, health-conscious individuals are wearing small digital pedometers and exercise monitors. Indeed, some companies such as Nissan in Japan give such devices to employees to heighten health awareness and decrease medical insurance costs. In the future, people who dress for success may also wear a healthwear personal trainer that helps keep them active, knowledgeable, and involved.


*Figure 1. MIThril system. Plugging the biosensor hub into a cell phone or wireless PDA provides a system that offers input, output, and general computation functions and can support a wide range of physiological measurements.*

## Opportunities and concerns

As new sensor, computing, and communication technology becomes available, healthcare professionals will be able to organize huge medical databases for use in tracking every test taken and medicine prescribed over an individual's lifetime. In addition to helping drive down healthcare costs, this data can provide powerful epidemiological information for use in improving our knowledge about keeping society healthy. For example, today because the huge expense of clinical trials limits the size and sensitivity of drug testing, harmful interactions are often detected only months or years after a drug is introduced to the general populace. Continuous, quantitative behavior logging has the potential to generate enough data so that researchers could discover these interactions more quickly.

Another application that is potentially even more important is the early detection of epidemics like SARS or biological weapons attacks. Today, reports of the treatment of an unusual number of patients with similar symptomatology at a medical facility often provide the first warning of a potential epidemic. Widespread continuous monitoring could detect such outbreaks much sooner by noticing when unusual numbers of people are behaving lethargically or staying home from work.

However, creating such an information architecture requires safeguards to maintain individual privacy. Indeed, we believe that this issue demands immediate, thoughtful attention and public debate, perhaps beginning with the current concern about using cell phone signals to track people. The current forces for creating huge databases and big medicine are powerful and all too successful. The potential solution is to place control and ownership of as much personal information as possible in the hands of the individual user, sharing only information cleansed of identifying features. This power-to-the-people approach favors using wearable sensing devices rather than sensors in the surrounding environment because the information starts out in the control of the individual, and the legal tradition in the US is that individuals own the data collected from their bodies.

## MITHRIL

In J.R.R. Tolkien's Middle Earth stories, *mithril* is a precious metal used to craft armor with properties that protect its wearer from evil. The term thus seems an apt name for the technology that provides the basis for healthwear. Highly flexible, the MIThril architecture provides a modular system tied together by wireless networking protocols and a unified multiwired-protocol power and data bus for sensors and peripherals.[1]

## Hardware components

Figure 1 shows the MIThril system. Designed for use with either a modern programmable cell phone or a wireless personal digital assistant (PDA), MIThril offers input, output, and general computation functions and can support a wide range of physiological measurements.[1,2] The MIThril hardware architecture is designed to be modular and easily configurable so that it can handle a variety of sensors and tasks. The software architecture supports using the ad hoc, on-the-fly combination of sensor signals from multiple users to control signaling and outputs.

A sensor hub interfaces with the MIThril body bus, which combines the Philips I2C multiple-device serial protocol and power lines. The sensor hub provides a bridge to the sensor data, enabling data acquisition, buffering, and sequencing, and it can be used as a stand-alone data-acquisition system.[2] This is particularly useful for large-group applications that do not require real-time processing, wireless communication between users, or

The core MIThril software components provide the foundation for developing modular, distributed, context-aware wearable and ubiquitous computing applications.

complex user interaction and thus do not require a cell phone or wireless PDA to be part of the system.

Currently supported devices include accelerometers for motion detection, IR active-tag readers for location and proximity detection, audio input and output devices, battery monitors, GPS, analog two-channel EKG/EMG, two-channel galvanic skin response sensors, and skin-temperature sensors. MIThril uses an RS-232 interface to communicate with a wide range of commercially available sensors for monitoring pulse oximetry, respiration, blood pressure, EEG, blood sugar, and $CO_2$ levels.

### Software architecture

The core MIThril software components include the Enchantment Whiteboard, the Enchantment Signal system, and the MIThril Real-Time Context Engine. These tools provide the foundation for developing modular, distributed, context-aware wearable and ubiquitous computing applications.

The Enchantment Whiteboard implements an interprocess communications system suitable for distributed, lightweight, embedded applications. Unlike traditional interprocess communications systems such as RMI and Unix/BSD sockets—which are based on point-to-point communications—the Enchantment Whiteboard uses a client-server model in which clients post and read structured information on a whiteboard server. This lets any client exchange information with any other client without the attendant complexity in negotiating direct client-to-client communication. These exchanges can take place without the client knowing anything at all about the other clients.

Clients can subscribe to portions of the Enchantment Whiteboard, automatically receiving updates when changes occur. Further, clients can lock a portion of the whiteboard so that only the locking client can post updates. It also supports symbolic links across servers, letting whiteboards transparently refer to other whiteboards across a network.

Intended to act as a streaming database, the Enchantment Whiteboard captures the current state of some system, person, or group. On modest embedded hardware, the board can support many simultaneous clients distributed across a network while making hundreds of updates a second. We have used the Enchantment Whiteboard with the Enchantment Signal system for bandwidth-intensive voice-over-IP-style audio communications between teams of up to 50 users.

## LIFE PATTERNS

The MIThril system provides a modular framework for real-time understanding of sensor data. The results of this process can be used locally for reminders and wearer feedback, or they can be broadcast to other users to enable smart-group communications and increased awareness of other members' health and activity levels. Pattern recognition techniques are the basis for modeling and interpreting the output of the wearable sensors. The standard pattern-recognition approach breaks this process into four stages:

- *Sensing.* A digital sensing device measures something in the real world, resulting in a digital signal of sampled values. For example, a microphone sensor converts continuous fluctuations in air pressure—sound—into discrete sampled values with a specified resolution, encoding, and sampling rate.
- *Feature extraction.* A raw sensor signal is transformed into a feature signal more suitable for a particular modeling task. For example, the feature extraction stage for a speaker-identification-classification task might involve converting a sound signal into a power-spectrum feature signal.
- *Modeling.* A generative or discriminative statistical model—such as a Gaussian mixture model, Support Vector Machine hyperplane classifier, or hidden Markov model—classifies a feature signal in real time. For example, a Gaussian mixture model could be used to classify accelerometer spectral features as walking, running, sitting, and so on.
- *Inference.* The results of the modeling stage, possibly combined with other information, are fed into a Bayesian inference system for complex interpretation and decision making.

We use machine-learning techniques to record raw sensor measurements and create statistical models of users' behavior and the surrounding context. Most commonly, we use hidden Markov models—which are also the basis of speech recognition systems—for behavior modeling. We have used this approach to build systems that use sensor measurements of hand motions to perform real-time recognition of American Sign Language and even to teach simple T'ai Chi movements.[3] Typically, these systems have vocabularies of 25 to 50 gestures and a recognition accuracy greater than 95 percent.

We have applied this same basic approach to audio and video to accurately identify the setting in which conversations take place—in a restaurant, in a vehicle, and so on—and even to classify the type of conversations a user engages in during the day.[4,5] Once we model the behavior and situation, we can classify incoming sensor data to build a model of the user's normal behavior. We can then use this model to monitor health, trigger reminders, or even notify caregivers.

Information about the wearer's social interactions is particularly interesting. Understanding face-to-face encounters is critical to developing interfaces that respect and support the wearer's social life. Social interactions are also very sensitive indicators of mental health. Thus, an important challenge for our behavior modeling technology is to build computational models that we can use to predict the dynamics of individuals and their interactions. The number of parameters is a significant factor in a model's learnability and interpretability.

The requirement for minimal parameterization motivated our development of coupled hidden Markov models (CHMM) to describe interactions between two people, where the interaction parameters are limited to the inner products of the individual Markov chains.[6] As a practical matter, a CHMM is limited to the interactions between two people. We have therefore begun using a generalization of this idea, called the "influence model," which describes the connections between many Markov chains as a network of convex combinations of the chains.[7] This allows a simple parameterization in terms of the "influence" each chain has on the others, and we can use it to analyze complex phenomena involving interactions between large numbers of chains.

To apply the influence model to human networks, we have extended the original formulation to include hidden states and to develop a mechanism for learning the model's parameters from observations.[8] Modeling human behavior this way allows a simple parameterization of group dynamics in terms of the influence each person has on the others, and we have found that it provides a sensitive measure of social interactions.

## HEALTHWEAR APPLICATIONS

Several ongoing projects hint at the capabilities healthwear will offer. These applications include medical monitoring and feedback systems for those with chronic medical conditions, monitoring social networking to reinforce healthy behavior, and mental monitoring to detect the symptoms of depression or dementia.

### Medical monitoring and feedback

Healthwear promises to be especially effective for monitoring medical treatments. Currently, doctors prescribe medications based on population averages rather than individual characteristics, and they check the appropriateness of the medication levels only occasionally—and expensively. With such a data-poor system, it is not surprising that medication doses are frequently over- or underestimated and that unforeseen drug interactions occur. Stratifying the population into phenotypes using genetic typing can improve the problem, but only to a degree. Continuous monitoring of motor activity, metabolism, and so on can be extremely effective in tailoring medications to the individual.

**Understanding face-to-face encounters is critical to developing interfaces that respect and support the wearer's social life.**

For example, consider Parkinson's patients. For them to function at their best, their medications must be optimally adjusted to the diurnal variation of symptoms. For this to occur, the managing clinician must have an accurate picture of how the patient's combined lack of normal movement (hypokinesia) and disruptive movements (dyskinesia) fluctuates throughout a typical day's activities.

To achieve this, we combined the MIThril system's wearable accelerometers with standard statistical algorithms to classify the movement states of Parkinson's patients and provide a timeline of how those movements fluctuate throughout the day.

Two pilot studies were performed, consisting of seven patients, with the goal of assessing the ability to classify hypokinesia, dyskinesia, and bradykinesia (slow movement) based on accelerometer data, clinical observation, and videotaping. Using the patient's diary as the gold standard, the result was highly accurate identification of bradykinesia and hypokinesia. In addition, the studies classified the two most important clinical problems—predicting when the patient "feels off" or is about to experience troublesome dyskinesia—perfectly.[9]

### Memory glasses

Regardless of age, we've all had our moments of forgetfulness. We accept such memory lapses as human fallibility, but we would be grateful if researchers could find a way to cue our natural memory and help us overcome these lapses. Perhaps such a device also could, for example, help improve an elderly person's memory or provide critical cues for emergency medical technicians, doctors, or firefighters in a nondistracting way.

Toward this end, we are developing *memory glasses* that might someday help people with chal-

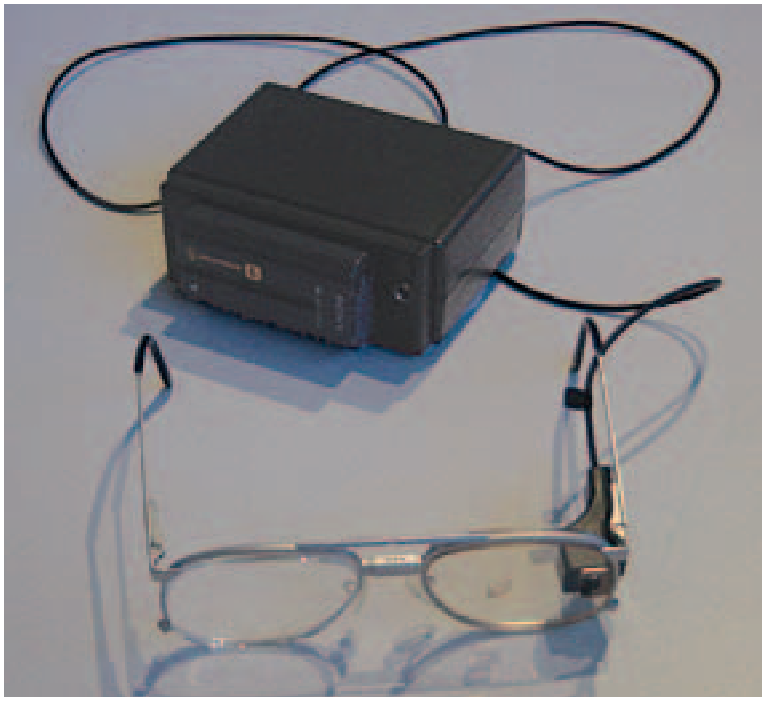

Figure 2. Memory glasses. A wearable, proactive, context-aware memory aid, the memory glasses system combines the MIThril platform with wearable sensors to provide a device that functions like a human assistant, storing reminder requests and delivering them under appropriate circumstances.

lenges ranging from complex memory loss to simple absent-mindedness. Figure 2 shows a prototype of this wearable, proactive, context-aware memory aid based on the MIThril platform and wearable sensors.[10]

Memory glasses function like a reliable human assistant, storing reminder requests and delivering them under appropriate circumstances. Such a system differs qualitatively from a passive reminder system such as a paper organizer, or a context-blind reminder system such as a modern PDA, which records and structures reminder requests but which cannot know the user's context.

Perhaps the major obstacle to this vision is that people resist being reminded to exercise, take their medicine, or skip that extra helping of dessert. Subliminal memory aids—visual and audio reminders that lie just below the user's threshold of perception—may offer one way around this problem. Our research shows that under the right conditions, subliminal text or audio cues can jog the memory much like overt cues *even though the person receiving the cues is not aware of them*. In one experiment, for example, subliminal text cues improved performance on a name-recall task by 50 percent compared to the uncued control.[11] Perhaps more important than this positive effect, our research suggests that incorrect or misleading subliminal cues do not interfere with memory recall. This contrasts starkly with the effect of overt miscues, which have a significant misleading effect.

A practical system might use a Bluetooth connection between cell phones to obtain the names of nearby friends. Similarly, a combination of information about location, proximity to others, time, and surrounding sounds could assist in situation recognition. The system could then use this context information to trigger the appropriate prompt, which would flash across the user's glasses or be communicated through an earpiece. If the system presented the prompt subliminally, users would not consciously process the reminder and so would be unaware that the prompt was jogging their memory. Thus, the subliminal prompts that the memory glasses provide would not interrupt a user's daily routines.

## SOCIAL NETWORKING

Reinforcing an individual's social support system may be the most effective way to encourage adopting more healthy behavior patterns. Thus, one aspect of healthwear's core functionality is interpersonal communications supported by continuous biomedical sensing.[12]

### Embedded social networking

Healthwear's social networking capabilities answer broad and immediate needs. For example, aging parents now commonly live far away from their families. Healthwear can help in such a situation by promoting communication between family members when it senses a suspicious change in an elder member's behavior.

In one version, healthwear occasionally but continuously leaves phone messages reminding grown children to call their parents and vice versa. However, when a marked change in behavior occurs—such as decreased food consumption, socializing, or sleeping—healthwear increases the frequency of these reminders. The system would not tell people something is specifically wrong or describe why it left a particular message, nor would it call the doctor except in extreme circumstances, because doing so could violate people's privacy and might actually interfere with proper medical support. Instead, healthwear strengthens the social support network when the need is likely to be most significant.

### DiaBetNet

Children also need social support networks, and they tend to be extremely sensitive to social context. We focused on this tendency when we created DiaBetNet, a computer game for young diabetics that uses belt-worn motion sensors, a wireless Internet connection, and a standard PDA for an interface.[13] DiaBetNet capitalizes on their passion for social games to encourage children with diabetes to keep track of their food intake, activity, and blood sugar level.

A typical day in the life of a diabetic child using

DiaBetNet would unfold as follows. In the morning, the child clips his wireless accelerometer and DiaBetNet case—with wireless Internet connection, PDA, glucose meter, and wireless receiver for the accelerometer—onto his belt and goes off to school. Throughout the day, the PDA records his activity from the accelerometer, data from measuring glucose and injecting insulin from the glucose meter, and user-entered information about food consumption. At any time, the user can see a graph on the PDA that summarizes the day's activity, carbohydrate consumption, and glucose data. From time to time, a wireless Internet connection sends this data to a secure central server.

DiaBetNet is a group gaming environment that requires guessing blood-sugar levels based on information that wearable sensors collect: The more accurate the answers, the higher the score. For example, imagine that a user named Tom begins to play DiaBetNet with others on the wireless network. Transformed into his cherished alias, Dr. T, Tom finds that his fellow players were all within 30 milligrams per deciliter of guessing their blood sugar levels correctly, but his guess was closer than anyone else's.

Tom challenges a DiaBetNet player called Wizard and looks through Wizard's data. Although Wizard was euglycemic in the morning, he ate a late lunch. Therefore, Tom decides that Wizard's glucose level would be high and guesses 150 mg per dl. Wizard guesses his glucose to be 180 mg per dl. Tom wins again and grabs five more points. He shoots a brief conciliatory message to his vanquished foe and signs off.

In clinical trials, 93 percent of DiaBetNet participants successfully transmitted their data wirelessly to the server. The Game Group transmitted significantly more glucose values than the Control Group. The Game Group also had significantly less hyperglycemia—glucose 250 mg per dl—than the Control Group. Youth in the Game Group displayed a significant increase in diabetes knowledge over the four-week trial. Finally, more youth in the Game Group monitored their hemoglobin levels.[14]

## Mental monitoring

Healthwear technology also can assist in the early detection of psychological disorders such as depression. Even though they are quite treatable, mental diseases rank among the top health problems worldwide in terms of cost to society. Major depression, for instance, is the leading cause of disability in established market economies.[15]

Researchers have long known that speech activity can be affected in pathological states such as depression or mania. Thus, they have used audio features such as fundamental frequency, amplitude modulation, formant structure, and power distribution to distinguish between the speech of normal, depressed, and schizophrenic subjects.[16] Similarly, movement velocity, range, and frequency have been shown to correlate with depressed mood.[17]

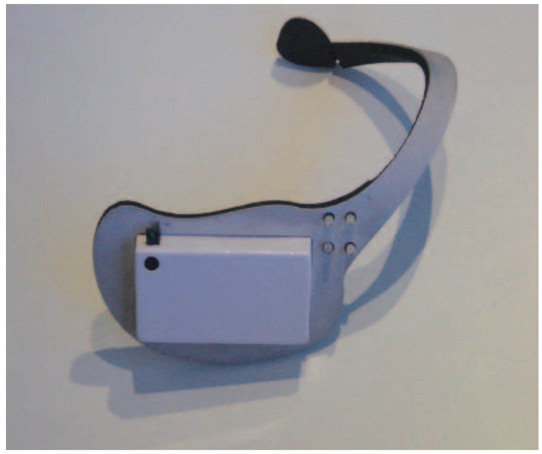

***Figure 3. MIThril-based sociometer. A biosensor hub in the badge-like device, which is worn over the shoulder, collects data about the wearer's daily interactions.***

In the past, performing such measurements outside the laboratory was difficult given the required equipment's size and ambient noise. However, today even common cell phones have the computational power needed to monitor these correlates of mental state. We also can use the same methodology for more sophisticated inferences, such as the quantitative characterization of social interactions. The ability to use inexpensive, pervasive computational platforms such as cell phones to monitor these sensitive indicators of psychological state offers the dramatic possibility of early detection of mental problems.

Perhaps the most sensitive measure of mental function is social interaction, which clearly reveals attitudes, emotions, and cognitive function.[18] To investigate this idea, we are using a MIThril-based device dubbed the *sociometer* to collect data about daily interactions with family, friends, and strangers such as:

- How frequent are the interactions?
- Are the interactions energetic or lethargic?
- Are the interactions appropriate without long gaps or frequent interruptions?

Figure 3 shows an example of the sociometers that we used to collect almost 1,700 hours of interaction data from 23 subjects. Participants in this study also filled out a daily survey that provided a list of their interactions with others.

The sociometer and conversation-detection algorithms classified 87.5 percent of the conversations as greater or equal to one minute, a far greater accuracy than achieved using the survey method.

The few conversations that the automatic sociometer method missed typically took place in high-noise, multiple-speaker situations.[19]

Once collected, researchers can use the *influence model*, a statistical framework that is a generalization of the hidden Markov models commonly used in speech recognition, to model the interaction data. Modeling spoken behavior this way allows a simple parameterization of group dynamics in terms of the influence each person has on the others. Our initial experiments show that these influence parameters are effective indicators of status within a social network and the degree of coupling to the social network.[20]

Judging from the adoption rates of advanced cell phones and wearable health tools such as pedometers, within this decade much of the US population will likely have access to continuous, quantitative monitoring of its behavioral health status, coupled with easily accessible biosignals. How will this change our lives and our society?

An exciting possibility is that with the widespread adoption of healthwear, researchers could, for the first time, obtain enough data to really understand health at a societal level. For example, correlating a continuous, rich source of medication data from millions of people could make drug therapies more effective and help medical professionals detect drug interactions more quickly. If correlated with medical conditions, the data could illuminate the etiology and preconditions of disease far more powerfully than is possible today and, further, serve as an early warning system for epidemic diseases like SARS. Comparing the medical data with genomic and protonomic data from different population samples could provide a powerful method for understanding complex gene and environment interactions.

However, when considering the effects of healthwear systems, we would be wise to recall Marshall McLuhan's dictum that "the medium is the message." The way in which a new technology changes our lifestyle may well be more important than the information it conveys.

Healthwear will likely be considered more personal and intimate than traditional health tools because it will form a constant part of a user's physical presence. Psychological studies have shown that clothes do indeed make the man. Thus, healthwear will not only be part of what the user wears but part of who that user *is*. Body-worn technology will likely change our self-perception and self-confidence in ways that are today unpredictable.

While it could be more effective at promoting healthy behavior than traditional approaches, healthwear also could be more seriously abused. However, with more than one billion cell phones already being worn every day, there is no escape from being absorbed into this far more intimately connected new world. Our goal now should be to design this technology to make that world a very human place to live. ■

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